Flight Delays

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1 Introduction

Flight delays pose significant challenges to the aviation industry, impacting not only economic performance but also environmental and social aspects. A critical factor in contributing to flight delays is adverse weather conditions. Previous studies, such as those by Kim and Park (2024), Kiliç and Sallan (2023), and Goodman and Small Griswold (2019), have highlighted the complex interaction between meteorological conditions and aviation operations, employing various machine learning (ML) and data-driven approaches to forecast delays. As air travel demand grows and adverse weather conditions become more frequent due to climate change, the ability to accurately predict and manage these disruptions is increasingly crucial. We seek to answer the question: are we able to improve upon the prediction accuracy of current machine learning models in order to best mitigate the challenges associated with flight delays?

Goodman and Small Griswold (2019) provided a detailed analysis of the impact of specific weather types and severities on delays and cancellations across 77 U.S. airports, emphasizing the critical role of extreme weather events. Their study found that weather was responsible for 32.6% of the total delay minutes recorded in the National Airspace System (NAS) from 2003 to 2015, with severe weather causing up to 82% of delay minutes in some instances. They identified freezing conditions, thunderstorms, and fog as the most disruptive weather phenomena, with departure delays averaging 83 minutes during freezing events and up to 98 minutes during fog at specific airports such as Miami (MIA) and Phoenix (PHX). Their findings emphasized the importance of understanding local weather patterns and airport-specific vulnerabilities to optimize flight schedules and improve operational efficiency.

Kiliç and Sallan (2023) examined arrival delays across the United States airport network using logistic regression, random forest, gradient boosting machine (GBM), and feed-forward neural networks. Their analysis, based on 2017 flight and weather data from the Bureau of Transportation Statistics and the National Oceanic and Atmospheric Administration, found the GBM model to be the most effective, outperforming others in terms of accuracy, F1 score, and area under the receiver operating characteristic curve (ROC AUC). Although their study covered a larger geographic area, it mainly focused on classifying delays and faced challenges with imbalanced data and limited real-time data use.

Kim and Park (2024) expanded the scope by applying a suite of ML models—including Decision Trees, Random Forest, Support Vector Machines (SVM), K-nearest Neighbors (KNN), Logistic Regression, Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) networks—to predict departure delays at three major international airports: Incheon (ICN), John F. Kennedy (JFK), and Chicago Midway (MDW). Their models achieved high predictive accuracy, with rates of 0.749 for ICN, 0.852 for JFK, and 0.785 for MDW in 2-hour forecasts. Although their study demonstrated the potential of ML models in long-term delay predictions, it was limited by its focus on individual airports and a reliance on historical datasets from 2011 to 2021, which may not fully capture future or emerging trends in weather patterns.

Building on these foundational studies, our research aims to address the limitations of previous work by integrating recent, high-frequency data across a more diverse range of U.S. airports, including both major hubs and regional airports. Unlike previous studies that focused on single airports or had limited data, we will use advanced model aggregation and real-time data integration to improve prediction accuracy and generalizability. After using our advanced data aggregation techniques, we will be able to create machine learning models that improve upon the prediction accuracy of current models. By developing models that account for the dynamic interactions between weather conditions and flight delays, we seek to provide stakeholders with actionable insights to reduce delay-related costs and improve overall passenger satisfaction. This research will not only advance the current state of delay prediction but also contribute to the broader field of transportation analytics, offering scalable solutions for mitigating weather-related disruptions across various modes of transportation.